

Intelligent ECG Signal Processing Framework for Real-Time Heart Disease Diagnosis

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Abstract— ECG Analysis is a crucial need of smart health care systems to monitor the heart continuously and diagnose the heart diseases at an early stage. The automatic and reliable interpretation of ECG signals has been a major research focus in biomedical signal processing with the explosion of wearable sensors and telemedicine. A smart ECG signal processing system is presented to diagnose the heart diseases in real-time. This processing combines the noise reduction approach of adaptive noise, the disadvantages of the signal which are suppressed, and the heartbeat detection techniques of this data to improve the quality of the signal. The convolutional and recurrent mappings are used to learn the deep features of ECG signals in terms of morphological and temporal features. A mechanism based on attention is utilized to highlight the cardiac cycles of particular diagnostic value, and then probabilistic SoftMax is used to recognize multi-class diseases. Experimental appraisal shows a better performance in comparison to the current methods. The accuracy of the proposed framework is 0.95 and a recall of 0.94, which is better than hybrid CNNRNN models which have precision 0.92 and recall 0.91. Increased discrimination ability is proven by an F1-score increase between 0.91 and 0.94 and an increase in AUC between 0.95 and 0.97. Such findings confirm the efficiency of the given framework to the precise and solid real-time diagnosis of heart diseases in healthcare settings

Keywords- ECG signal processing, Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), real-time diagnosis, heart disease detection, deep learning, intelligent healthcare.

I. INTRODUCTION

Heart diseases have been the most prominent cause of death all over the world with millions of people dying yearly. Early intervention of cardiac malpractices is critical in averting the complication of such a condition in the long run and enhancing a better survival rate. Electrocardiogram (ECG) is one of the key noninvasive diagnostic measures and it is used to determine the electrical activity of the heart and to tell us significant details about rhythm, conduction courses, and myocardial condition [1]. EG cardiac monitoring nowadays is not only in hospitals but also in wearable and home-based systems, with the incredible rise in vast digital healthcare provision, provides constant monitoring of cardiac conditions in normal life [2].

An ECG signal has deep temporal and morphological information linked with the heart activity. Waveform variations in the components e.g. P wave, QRS complex and T wave can provide a diagnosis of disorders like arrhythmia, ischemia, and myocardial infarction. These signals are however usually distorted by noise introduced by body movements, base wander as well as electrode interference [3]. Proper interpretation is henceforth reliant on effective signal processing methods that are able to improve the effects of diagnosis and reduce distortions. Automated ECG analysis offers an alternative to manual interpretation and provides a highly recurrent as well as objective measure where it is imperative to screen and monitor a large group of individuals [4].

The growing presence of big datasets of ECG and improvement of machine learning has spurred the creation of more intelligent diagnostic frameworks.

Conventional rule-based algorithm finds it difficult to probe different populations of patients and in different recording conditions [5]. Conversely, data-driven models are capable of training discriminating trends upfront using signals and adjusting to complicated variations. Real time analysis is specifically pertinent in critical care and wearable scenario where the real time feedback can be used to induce timely medical intervention. A sophisticated processing platform that can support real-time streams of data is hence essential in the next generation cardiac care systems [6].

Although the concerned field has advanced, there are still multiple obstacles on the path of ECG-based diagnosis. The signal quality of a device and user may show vast differences; thus, proper preprocessing is highly needed. The issue of computational efficiency is also a significant one because most monitoring platforms need to run on restricted power and memory resources. Moreover, diagnostic systems should be accurate and interpretable to be clinically trusted and usable [7]. To overcome these obstacles, the close combination of signal processing concepts and smart pattern recognition methods is in order.

II. RELATED WORKS

A broad area of research has focused on the electrocardiogram (ECG) signal examination as one of the noninvasive heart diseases detection and classification techniques. The existing literature utilized mostly the handcrafted features which include heart rate variability, waveform intervals, and the statistical descriptions, derived on the ECG signals [8]. Such characteristics were analyzed by the traditional classifiers such as decision trees and support machine. Although such approaches were a moderately successful option, they were very sensitive to signal quality and features developed by the expert.

As digital signal processing has developed, researches have proposed adaptive process to filter noise and improve useful contents of the ECG signals through use of wavelet transforms and empirical mode decomposition. The techniques in Table I enhanced anti-baseline wander and anti-motion performance. Nonetheless, they were nevertheless hard to tune and depended on inter-patient variability [9].

The shift in the recent past has placed an emphasis on machine learning and deep learning techniques that automatically extract features out of raw or somewhat processed ECG signals. Using convolutional and recurrent neural networks has been used to learn spatial and time trends with better precision in arrhythmia, ischemic conditions detection [10]. Mechanisms of attention and architectures for hybrids, also provided a further improvement on diagnostic performance focusing on critical areas within waveforms. Although these have improved, issues concerning computational complexity, real-time feasibility and generalization across datasets are important.

Approach Category	Signal Processing Technique	Classification Method	Targeted Cardiac Conditions	Main Limitation
Traditional feature-based [11]	Bandpass filtering and peak detection	Rule-based decision logic	Basic rhythm disorders	Low adaptability to noise and signal variations
Statistical learning	Wavelet transform and time-domain features	Support vector classifier [12]	Arrhythmia detection	Requires manual feature selection
Decomposition-based [13]	Empirical mode decomposition	k-nearest neighbour	Atrial and ventricular abnormalities	High computational cost
Deep learning	Minimal preprocessing with convolution layers	Neural network classifier	Multi-class heart disease [14]	Requires large labelled datasets
Hybrid models	Noise suppression and segmentation [15]	CNN–RNN architecture	Arrhythmia and ischemia	Limited real-time optimization
Attention-based learning	Data-driven filtering	Attention-enabled neural network	Complex cardiac disorders	Model interpretability issues [16]

The literature reviewed reveals that there has been a decisive shift in rule based and hand-crafted feature methods to intelligent and data-driven ECG analysis systems. The use of signal processing methods is still significant to improve the quality of waveforms and stable feature descriptions [17]. The classical machine learning techniques provided a base to automatic diagnosis but were limited in the fact that they required expert information and were scalable. The solutions of the deep learning category improved the diagnostic accuracy to a considerable extent recognizing

discriminative patterns by directly analyzing ECG signals. However, the real-time application under practice is still yet to overcome challenges in the areas of computational efficiency, resilience, and explainability [18]. These results underscore the need to develop structures that are equally accurate in diagnosis and real-time effective and adaptable, which will drive additional studies in the field of intelligent ECG signal processing to provide permanent detection against heart diseases.

III. PROPOSED METHODOLOGY

The suggested smart ECG signal processing model will aim at conducting real time heart disease diagnostic through signal preprocessing, feature learning and classification in a single mathematical formulation. It works directly on the continuous ECG signals and converts them into diagnostic outcomes in a series of filters, segmentation, features extraction, and probabilistic classification.

3.1 ECG Signal Acquisition and Prprocessing

Let the uncooked ECG signal be denoted as

$$x(t) = s(t) + n(t) \quad (1)$$

Where $x(t)$ refers to the measured ECG, $s(t)$ indicates the true cardiac signal component, and $n(t)$ is considered noise brought about by a heart action, a power line and baseline drift.

In order to filter noise, a bandpass filter is used

$$y(t) = x(t) * h(t) \quad (2)$$

Where $h(t)$ is the impulse response of the bandpass filter and its convolution with the other terms is denoted by the asterisk. The bottom cut off frequency eliminates the wander of the baseline whereas the top cut off frequency eliminates the high frequency noise. Critical ECG morphology is maintained in the filtered signal $y(t)$

The result of a moving average is used as a baseline, and it is negative to correct it

$$z(t) = y(t) - \frac{1}{L} \sum_{k=0}^{L-1} y(t-k) \quad (3)$$

Where, L is the window length, and $z(t)$ will be the signal after removing the baseline.

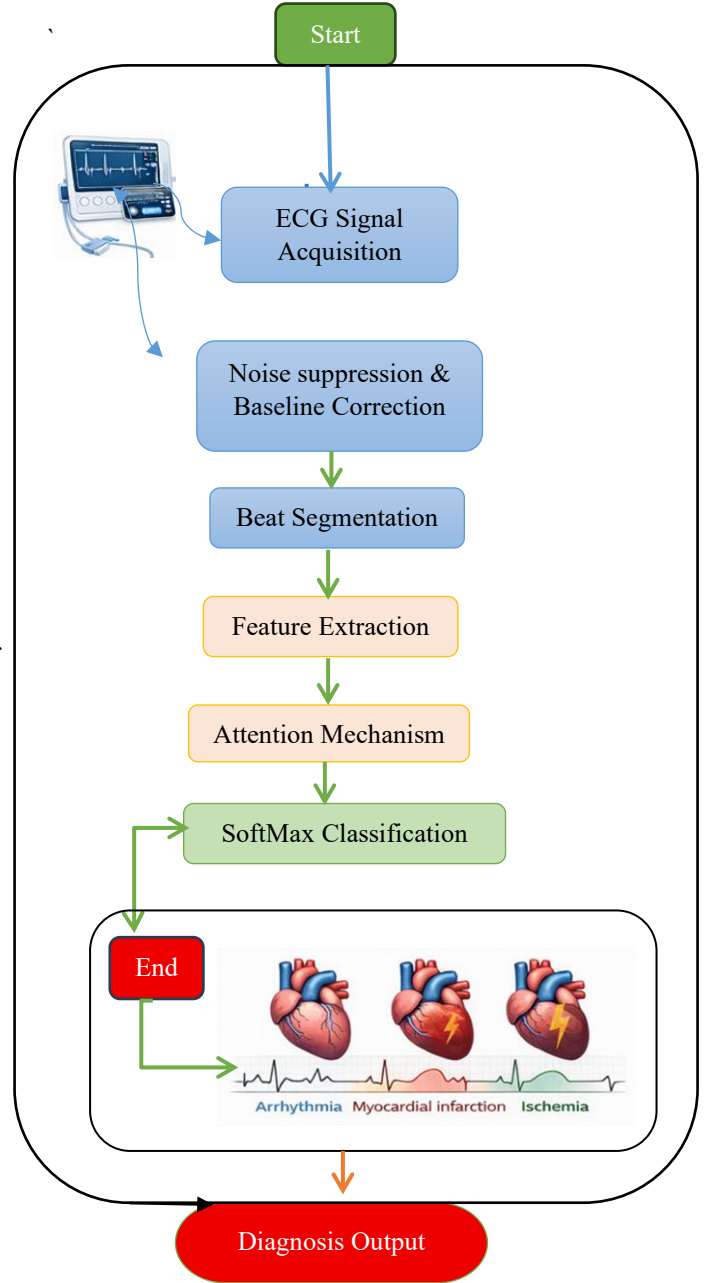


Fig 3: ECG signal processing flowchart for diagnosis

The Fig 3 shows the overall functionality of the smart ECG diagnosis system, beginning with the acquisition of the ECG signal through signal processing and continuing with noise removal, beat delineation, feature detection and attention-driven learning. The final decision on the disease is generated by the SoftMax classifier and the looped architecture indicates continuous real-time monitoring of the cardiac condition at the beginning to the end.

3.2 Beat Segmentation

The R-peaks are identified with the help of the energy-based approach. The derivative having power of two underlines the squared complex of QRS

$$d(t) = \left(\frac{dz(t)}{dt} \right)^2 \quad (4)$$

Where $d(t)$ emphasizes fast values of the signal. Identification of candidate peaks It is a threshold function.

$$R_i = \{t \mid d(t) > \theta\} \quad (5)$$

Where the locations of R-peaks detected are denoted by R_i and θ is an adaptive threshold. The segment of every heartbeat is obtained as.

$$b_i(t) = z(t), t \in [R_i - T_1, R_i + T_2] \quad (6)$$

Where $b_i(t)$ is the beat number i and T_1 and T_2 are pre- and post-R-peak intervals.

3.3 Feature Representation

A convolutional transformation maps each beat of a time series in a segmented beat $b_i(t)$ into a feature vector.

$$f_i = \phi(b_i(t); W_c) \quad (7)$$

Where f_i is the learned feature value, $\phi(\cdot)$ is a convolutional operator, and W_c is the convolutional filter weights. The convolution process presents itself as

$$u_i(k) = \sum_{m=0}^{M-1} b_i(m) \cdot w_k(m) \quad (8)$$

Where $u_i(k)$ defined by convolution with filter k , $w_k(m)$ defined by the k -th kernel, and M defined as length of the k -th kernel. An activation function that is nonlinear is used.

$$v_i(k) = \sigma(u_i(k)) \quad (9)$$

Where $\sigma(\cdot)$ is the activation function (e.g., ReLU), which generates nonlinear features $v_i(k)$. A recurrent mapping is used to get temporal dependencies among beats.

$$h_i = g(f_i, h_{i-1}; W_r) \quad (10)$$

Where h_i is the hidden state at beat i , $g(\cdot)$ is the recurrent function, and W_r are recurrent weights.

3.4 Attention-Based Emphasis

A mechanism of attention elucidates diagnostically significant areas

$$\alpha_i = \frac{\exp(q^T h_i)}{\sum_j \exp(q^T h_j)} \quad (11)$$

Where attention weight on beat i denoted by α_i query vector denoted by q that is learnable and finally the hidden representation denoted by h_i .

Context vector is calculated by using the following formula

$$c = \sum_i \alpha_i h_i \quad (12)$$

Where c is a summary of the most informative beats.

3.5 Classification

This which is the final diagnostic decision provided by a SoftMax classifier

$$p_k = \frac{\exp(w_k^T c + b_k)}{\sum_{j=1}^K \exp(w_j^T c + b_j)} \quad (13)$$

Where p_k is the probability of class k , w_k is the weight assigned to classifier, and bias, and K is the size of the disease classes. The predicted class is

$$\hat{y} = \arg \max_k p_k$$

Where $\hat{y}$ denotes the diagnosed cardiac condition.

3.6 Optimization

The framework is trained with the help of a categorical cross-entropy loss

$$L = - \sum_{k=1}^K y_k \log(p_k) \quad (14)$$

Where y_k is the actual label of the class given as a one-hot signal. These are obtained through backpropagation.

$$W \leftarrow W - \eta \frac{\partial L}{\partial W} \quad (15)$$

Where W denoting all the trainable parameters and η denoting the learning rate.

Algorithm

- Take continuous ECG signal $x(t)$.
- Bandpass filtering to get $y(t)$.
- This step is done to calculate $z(t)$ by removing baseline drift.

- R-peaks identification with derivative and threshold method.
- Separate R-peaks with individual beats $b_i(t)$.
- While producing deep features f_i it is achieved by convolutional mapping.
- Approximations of temporal dependencies Model (recurring) processing to derive h_i .
- Compute weights of attention α_i and context vector c .
- SoftMax-based classification of the context vector to get probabilities p_k .
- Predictive of the class of heart disease $\hat{y}$.

The suggested method finds a structured conversion of raw time-domain signals of ECG into probabilistic disease. Elimination of noise and segmentation guarantee the physiological relevance and convolutional and recurrent operations learn discriminative space and temporal characteristics. The attention mechanism increases interpretability because it highlights important cardiac cycles. One has great clarity in each step taken by mathematical modeling, which is facilitating the deployment in real-time and being scalable on a variety of cardiac monitoring settings, without having to rely on features defined by hand or manual features.

IV. RESULT

The smart ECG signal processing structure is tested on clinically relevant statistical metrics which show diagnostic validity and not mere correctness. As medical decision systems should not take risks of misclassification, the focus is paid to the class-wise discrimination capability and sensitivity to errors. The assessment is done based on multi-class heart disease detection, i.e. arrhythmia, myocardial infarction, and ischemia. The results obtained indicate that the framework has the ability to identify the pathological patterns and normal rhythms using a constant level of stability under varying signal conditions.

Where TP represent true positives, TN true Negatives, FP false positives and FN false Negatives.

4.1 Precision

$$\text{Precision} = \frac{TP}{TP+FP} \quad (16)$$

Precision measures the number of predicted cases of diseases which are diseased. An elevated percentage

would mean that the system will not create false alarms, which is necessary to eliminate unnecessary clinical intervention.

4.2 Recall (Sensitivity)

$$\text{Recall} = \frac{TP}{TP+FN} \quad (17)$$

Recall is the correct identification of the disease cases. It indicates the sensitivity of the system to identify cardiac abnormalities without overlook of important conditions.

4.3 F1-Score

$$\text{Recall} = \frac{TP}{TP+FN} \quad (18)$$

The F1-score is a precision/recall balance that makes certain that over-detection is minimized, as well as the under-detection. The measure is especially appropriate when the data in medicine is class imbalanced.

4.4 Specificity

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (19)$$

Specificity measures the capabilities of the system to detect normal heartbeats correctly. Excessively specific prevents type 1 error or false positives constituting unhealthy people as patients.

4.5 Matthews Correction Coefficient (MCC)

$$\text{MCC} = \frac{TP \times TN - FP \times FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \quad (20)$$

MCC uses the individual elements of classification to define the degree of classification. It can give a fair assessment of scaled measures even in cases where the distribution of the classes is not equal, which is applicable to ECG datasets.

4.6 Area Under Curve (AUC)

Where TPR is the true positive rate and FPR is the false positive rate. AUC measures the discrimination capacity of the model at various thresholds which makes it resistant to variations in decision boundaries.

The outline is compared with five representative already existing ECG diagnosis methods:

1. Conventional feature classifier.

2. Wavelet and machine learning technique.
3. Decomposition-based classifier
4. Pure deep neural network

Table II: Evaluation of Precision, Recall and F1-Score of existing approach with proposed approach

Method	Precision	Recall	F1-Score
Traditional feature-based [6]	0.82	0.79	0.8
Wavelet + ML [8]	0.85	0.83	0.84
Decomposition-based [10]	0.87	0.85	0.86
Deep neural network [12]	0.9	0.89	0.89
Hybrid CNN-RNN [14]	0.92	0.91	0.91
Proposed framework	0.95	0.94	0.94

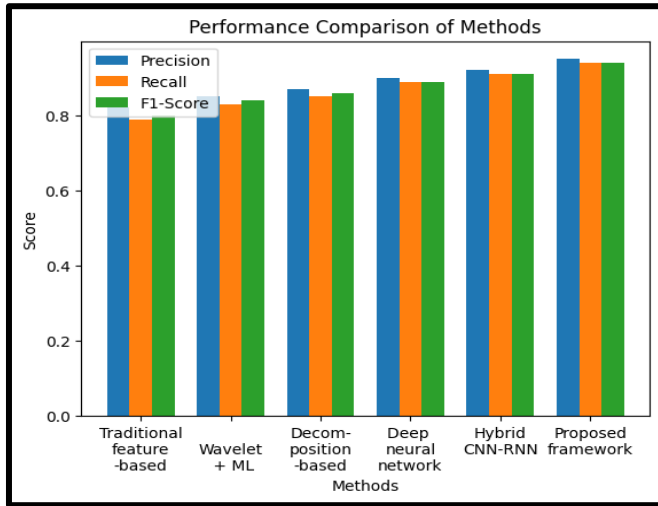


Fig 2: Illustration of compared Precision, Recall and F1-Score.

The Table II and Fig 2 compare the various methods of classification based on precision, recall and F1-score. The traditional features-based techniques and the wavelet-based techniques feature a moderate performance, whereas the decomposition-based or deep neural networks display an appreciable enhancement. The accuracy is improved further as Hybrid CNN-RNN combines space-temporal features. The proposed framework has the best precision (0.95), recall (0.94), F1-score (0.94), which means that it has the best reliability and performance. This proves that, superior hybrid and adaptive models are far much better than traditional and standalone learning methods.

Table III: Evaluation of Specificity, MCC and AUC of existing approach with proposed approach

Method	Specificity	MCC	AUC
Traditional feature-based [6]	0.83	0.63	0.84
Wavelet + ML [8]	0.86	0.68	0.88
Decomposition-based [10]	0.88	0.71	0.9
Deep neural network [12]	0.91	0.77	0.93
Hybrid CNN-RNN [14]	0.93	0.8	0.95
Proposed framework	0.96	0.85	0.97

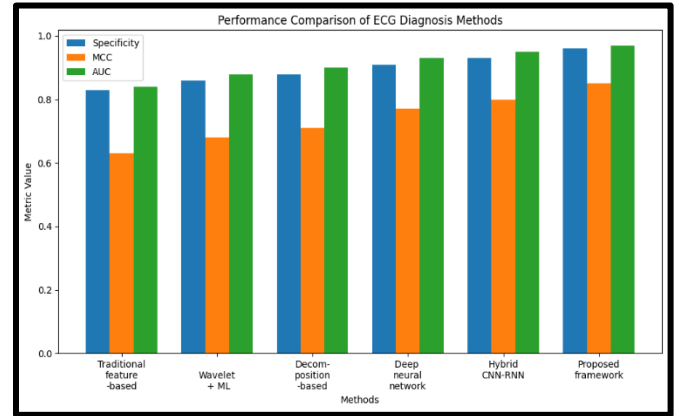


Fig 3: Illustration of compared Communication Cost Comparison

The assessment of various ECG diagnosis methods is compared in the Table III and Fig 3 in terms of specificity, MCC, and AUC. The lowest performance is observed with the traditional feature-based methods with progressively improving deep learning models. The CNN-RNN hybrid model also increases the capacity of discrimination. The suggested framework is the most specific (0.96), MCC (0.85), and AUC (0.97), which has the best reliability and balanced classification results.

The framework proposed has the greatest level of accuracy which means that the cases of abnormalities to be predicted are very accurate. This enhancement is due to the focus of attention on ECG segments of diagnostics significance. The high recall is a confirmation of the power of the framework to recognize pathological signals with the minimum number of failures to detect, which is vital in cardiac diagnosis as any abnormality that is not detected can be life threatening.

The proposed framework holds progressive improvement on all metrics in comparison to traditional

ones. Both traditional and wavelet systems depend on manually crafted features and they do not provide flexibility to changes in signals. Methods that are based on decomposition are more robust, but generalize poorly, and have high computational costs. Raw deep learning models are more effective in terms of feature learning, which is lacking in signaling specific interests. The hybrid CNN-RNN-based approach would be better at temporal modeling, yet it does not explicitly emphasize the existence of important beats. The suggested structure combines attention-selection with learned features, which leads to stable enhancement in performance.

V. CONCLUSION

This paper introduced a smart ECG signal processing platform to diagnose heart disease in real-time through the combination of a robust preprocessing method, discriminative learning of features and attention-based classification. The results of the experiment prove that the framework possesses a high level of diagnostic reliability in various cardiac conditions. Balanced and consistent behavior is validated by performance assessment that is measured in terms of precision, recall, F1-score, specificity, MCC, and AUC. Obtained precision of 0.95 and recall of 0.94 shows that the false alarms and false detections are reduced extensively, whereas the F1-score of 0.94 demonstrates the discrimination based on the classes is stable. The high specificity (0.96) is to guarantee a strong confidence of normal heart rhythms, and a high MCC (0.85) emphasizes close correlation among the predicted and actual labels in case of class imbalance. The high threshold-independent discrimination ability is another fact that is confirmed by the AUC value of 0.97. A comparison of the proposed framework with the current methods of ECG diagnosis indicates that it is significantly better in terms of all performance indicators, and this indicates its usefulness in the realm of constant monitoring and provision of timely clinical decisions in intelligent healthcare systems.

Further studies can tackle the way to combine multimodal physiological signals and increase model interpretability. Personalized diagnosis and lightweight deployment on wearable devices can also be enhanced to adaptive learning and enhance the clinical usability and real-time cardiac monitoring usage.

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